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Park J.

Lee J.

Lau H.

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Relationship Preserving Auction for Repeated e-Procurement

Jong Han PARK [a 1] Jae Kyu LEE [b] Hoong Chuin LAU [a]

[a] School of information Systems, Singapore Management University, 80 Stamford Road, Singapore

[b] KAIST Graduated School of Management, 87 Hoegiro, Dongdaemoongu, Seoul, Korea

(+65) 81266120 (+82) 2-958-3612 (+65) 68280229

jhpark@smu.edu.sg jklee@business.kaist.ac.kr hclau@smu.edu.sg

ABSTRACT

While e-procurement auction has helped firms to achieve lower procurement costs, auction mechanisms that prevail at present in procurement markets need to address an important issue that concerns the ability to maintain long term relationships with the partners, especially in repeated e-procurement settings. In this paper, we propose a Relationship Preserving Auction (RPA) mechanism that augments the conventional auction mechanism with a bidder relationship scoring model. Our proposed mechanism gives increased chances of winning to the bidders who have bidden at relatively competitive price but had comparatively less wins so far. Keeping these bidders in the auction over time will lead to more competitive bidding prices and eventually reduce the auctioneer's total procurement cost in repeated auctions. From simulation experiments, we show how RPA works under different bidders' behavior. We show that RPA is able to obtain lower procurement cost compared to conventional procurement auctions when bidders bid opportunistically and renege readily to other markets.

Keywords: Supplier relationship, e-procurement, auction

1. INTRODUCTION

E-procurement auctions are increasingly being used in B2B sourcing activities. Virtually every major industry has begun to utilize auctions for procurement on a regular basis. The increasing usage of e-procurement auction is based on two key factors. The first is that e-procurement auction creates financial savings for buying companies. These auctions have tended to produce typically 15% cost savings (Cohn 2000).

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The second factor influencing their rapid growth is the process efficiencies that auctions create. E-procurement auction reduces procurement time dramatically from 6 weeks to several hours (Jap 2002).

In forging long term contracts between buyers and sellers, partnerships have long been considered as the most appropriate strategy (Cousins, 1999; Burnes and New, 1997). In recent years, market mechanisms have emerged to be an attractive alternative. For example, Forker and Stannock (2000) demonstrated that there can be a better understanding between buyer and supplier in the 'competitive' exchange, and that market mechanisms may be a better method of satisfying the needs of contracting firms in many buying situations. As e-commerce grows, buyer's supply sources can be extended by adding more competition, with less additional transaction cost to the buyer (Clemons et al. 1993, Smart and Harrison 2003). Hence, we see the increased potential to use market mechanism such as auctions in the long term procurement market.

Although the wide adoption of current e-procurement auction has helped firms to obtain lower cost procurements, it has also raised important issues related to the ability to maintain long-term relationships with the partners in the supply chain. Hence, for auctions to be long sustaining, we argue that it is vital that the mechanism takes into consideration the aspect of relationship preservation. The meaning of relationship in auction market is different from its traditional meaning in SCM literature. The meaning of relationship in auction is restricted only between auctioneer and bidders in regard to the auction related activities.

Especially, maintaining long term relationship with bidders is necessary in repeated auctions with same bidders after the initial contract period. In this case, suppliers should be selected not solely on the basis of price but a multi attribute selection criterion like quality, reliability, and congruency with business goal (Daly and Nath 2005). Furthermore, to be a sustainable auction mechanism in repeated purchasing, the mechanism needs to help the auctioneer to maintain enough bidders for competitive bidding price over time (Smart and Harrison 2003). Keeping enough number of bidders are critical to lower the bidding price and eventually the procurement cost for auctioneer (Tenorio, 1993). Therefore, to design successful auction mechanism for repeated e-procurement market by considering relationship with bidders, there are two key factors:

[1] J. H. Park is currently a PhD candidate at KAIST Business School.

- Fair bidder assessment: we need to assess the bidders based on not only price but also quality, delivery time, reliability and their involvement
- Sufficient number of bidders: we need to maintain relationship with sufficient number of bidder in order to have competitive bidding price over repeated auctions.

The auction mechanism considering these two factors can increase the procurement cost for auctioneer in short term, but it will reduce the cost eventually in long term. Many researches for the fair bidder assessment have been done in Multi-attribute auction area. But research attempts for the second factor have been found rarely in auction studies. Hence, we mainly focus on designing auction mechanism helps to maintain enough bidders over repeated auctions in this research.

In this paper, we propose the notion of a ***Relationship Preserving Auction*** (RPA) which embeds attributes aimed at preserving long term relationship with enough number of competitive bidders in repeated auctions. To take into consideration of the relationship in auction mechanism design, we devised relationship scoring model for bidders based on their bidding behaviors and auction history. The relationship score provides greater winning opportunity to bidders who have bidden competitively but have not managed to win in previous auctions. Under this proposed mechanism, the buyer (or synonymously, auctioneer) can retain enough bidders to participate in the auction at competitive prices, while bidders will remain long enough in the system to be able to obtain a share of the revenue through successful bidding. We will show experimentally how RPA reaps the benefits arising from preserving relationship with bidders in repeated auction by comparing with other auction mechanisms under varying bidders' behavior.

The remainder of this article proceeds as follows. In section 2, we review related studies from various auction areas and supplier relationship management. In section 3, we set target market for our proposed mechanism. Descriptions of RPA are followed in section 4. In section 5, the experiment settings are explained and results are summarized with discussions. In section 6, we conclude by discussing the limitation of current works and the direction of future studies.

2. RELATED STUDIES

A typical auction is an economic mechanism for determining the price of an item in a one time transaction. In a corporate procurement setting, price is not a sufficient criterion to assess suppliers. Some researchers attempt to include not only price but also multiple attributes such as quality and delivery accuracy so as to evaluate suppliers more rigorously. Multi attribute auction mechanism contributes to evaluate bidders in multi dimensions, but still focusing on one-time purchase rather than long term relationship procurement (Martin Bichler et al. 1999).

Some researches have allowed multiple items in one auction. Auctions where bidders are allowed to submit bids on combination of items are called combinatorial auction (Peked and Rothkopf 2003). Combinatorial auction has recently received much attention in various area such as spectrum selling (McMillan 1994), airport time slot allocation (Rassenti et al. 1982), transportation auction (Seffi 2004) and even in procurement (Hohner 2003)., Combinatorial auction allows bidders to express its preference more precisely and allocates multiple items more efficiently in one time auction.

Often in procurement, preserving long term relationships between buyers and suppliers is a critical success factor for both sides (Grey et al. 2005). Many scholars and practitioners are reaching a consensus around a trade off between the value and benefits of gaining lower prices versus losing long term relationship with suppliers. Daly and Nath (2005) for instance suggested that the auction design can be more conductive to long term investments and relationships by subsidizing relational partners, making payments for losing bidders, even re-negotiating final contract bid prices and specifications. While their study is conceptual, what is needed is a more concrete methodology for designing and implementing relationship-centric auction mechanisms so as to tangibly demonstrate and reap the benefits arising from preserving long term relationship in repeated procurement auctions.

Lee and Szymanski (2006) used an incentive mechanism to keep enough bidders in a forward auction market. They proposed Optimal Recurring Auction (ORA) for e-service markets with multiple units and multiple winners. The auction mechanism considers not only price but also incentive score. They compare their auction mechanism with uniform price auction empirically and their results shows that keeping enough bidders is important even in recurrent forward e-service auctions. While their assumptions are somewhat unrealistic in generating experimental settings and data, the approach itself is quite interesting.

The impact of number of bidders on auction performance has been studied in auction research. McAfee and McMillan (1987) suggested that knowledge about the number of bidders and their bidding behavior matters in various auction mechanism and its results. Harstad et al. (1990) showed that each bidder selects his bid effectively knowing the number of rivals he faces in contingent bidding.

Airco Company's auction case (Smart and Harrison (2003)) shows that Airco achieved 30% reduction on its stationery procurement from the first auction which were far in excess of their expectation. This result is affected not only by adopting auction per se, but also other important factors which arise from the previous contract conditions and new entry of competitive suppliers. They reported that the previous contracts had been with the same supplier for 10 years and had not been put out to tender during that period. The situation turned around when several new suppliers have entered this market and supply in quite competitive price. The authors emphasized that to maintain such price impact by auction in subsequent contracts, keeping enough competitive bidders is critical (more so than adopting auction itself).

Hao (2000) presented key factors affecting an opportunistic bidding strategy: the cost distribution of all bidders, market demand, and the number of bidders participating in the auction. Experimentally, he shows that when the number of bidders increases, the probability of being on the margin and winning the auction is reduced and the bidding price will be reduced accordingly. Hence, in repeated procurement markets, maintaining enough number of competitive bidders is critical for buyer to reduce cost by auctions.

In supplier relationship management (SRM) studies, the importance of relationship with suppliers and the strategy to develop the relationship have been discussed substantially. Krause et al. (2000) mentioned four key activities to develop the relationship with suppliers: supplier incentives, supplier assessment, competitive pressure and direct involvement. In the context of auction mechanism design, we consider that bidder incentives based on its assessment through auctions can be adopted as an additional feature to encourage and retain long term relationship with suppliers.

3. TARGET MARKET ANALSYSIS

To classify our target market, we use two criteria; purchasing volume and purchasing frequency. Generally speaking, auction is suited for items with high purchasing volume which attracts many bidders to join and compete on price. The other criterion often neglected is the purchasing frequency where we argue that the auction mechanism needs to handle relationships when auction occurs repetitively and frequently. Figure 1 shows our target market position as well as recommended procurement strategy for each cell at the current market.

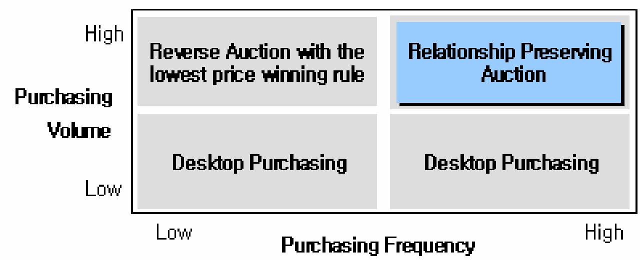

Figure 1. Target market classification

The upper left quadrant represents most manufacturing settings, where manufacturing companies open auctions for an item with high purchasing volume, but the frequency is very low. Our target market is the high purchasing volume with high frequency (upper right quadrant) which can be readily found in procurement outsourcing companies.

Procurement outsourcing company form groups of buyers of particular products or commodities within specific vertical or horizontal markets. By aggregating the buying power of multiple customer buyers, the procurement outsourcing company becomes a single *virtual* buyer with large enough volume to purchase and open auction frequently for the same item as required by her customer buyers. A buyer can often reap economies of scale and reduce its transaction cost by outsourcing their procurement to the procurement outsourcing company. Everest research (2007) reports that procurement outsourcing companies have grown rapidly and procurement outsourcing market grew to U.S. $40 in managed spend in 2006. In addition, buyers for an outsourcing company have realized sourcing-related savings of 5-20%. A vertical procurement outsourcing company pursues this buyer aggregation / purchasing outsourcing strategy in manufacturing inputs. For example, FOB.com pursues this strategy in chemicals; BizBuyer.com, PurchasingCenter.com and iMarketKorea are a few of many firms pursuing this strategy in horizontal markets (MRO procurement).

In this context, the procurement outsourcing company (auctioneer) opens multiple auctions for the same item because it has multiple customers with various demand curves. The buyer and suppliers are loosely coupled in the sense that suppliers will readily renege and move to another market if they do not derive enough revenues from the current market. From the procurement outsourcing company point of view, he needs to maintain enough suppliers in the auction so as to solicit competitive price bidding arising from competition among suppliers. The e-procurement auction mechanism we propose can help the procurement outsourcing company to maintain bidding price competitiveness in repeated auction by keeping enough number of bidders.

Our target auction problem is based on the typical single-shot first price sealed bid reverse auctions in a repeated procurement environment. We assume that there is a single buyer who is interested to procure a single item from multiple suppliers. The item is either a standardized or semi-standardized product. Multiple suppliers are invited to bid to supply multiple units of the item and only one winner will be assigned in one auction. The auctioneer and bidders are loosely coupled and bidders can drop out of the auction market if they cannot make enough revenue after certain number of auction participations

We make the following assumptions to simplify our study;

- The number of participants in an auction is known to all bidders
    - Most auctions models assume the number of bidders is common knowledge (Harstad et al. 1990)
    - Where these assumptions are not valid, it is often possible to make use of the best estimate or historical data to substitute the data assumed (Hao 2000).
- The set of bidders is pre-determined from the onset, and new bidders are not allowed to join in the ongoing repeated auctions
- A bidder is involved in every auction until he drops out of the repeated procurement environment..

4. RELATIONSHIP PRESERVING AUCTION (RPA) MECHANISM

The purpose of our proposed Relationship Preserving Auction is to maintain enough bidders for continuous competitive bidding price over repeated auctions. The goal is to help the auctioneer to reduce the procurement cost in long term eventually. For this purpose, we pick winners based on not only price but also *relationship score* calculated based on bidders' bidding history. Intuitively, the basic idea in relationship score is to give a higher score to a bidder whose bidding price was competitive enough but *did not* win in previous auctions. This score will give a higher chance to win for bidders whose bidding price is not the lowest at the current auction but has been relatively competitive in previous auctions to prevent bidders dropping out of the auction. To maintain efficient procurement auctions, the losing bidders must be kept interested and able to compete for future auctions (Daly and Nath 2005). Thus both price and relationship score are then considered in the winner determination process.

4.1 Relationship Scoring Model

There are n bidders, denoted by $i=1,\ldots,n$. Each bidder enters the bidding price b_1, b_2,…,, b_n, respectively in each auction. There are m auctions, denoted by $j=1,\ldots,m$. b_{ij} denotes bidder i's bidding price in the jth auction and n_j denotes the number of bidder participating in the jth auction.

We propose the following relationship scoring model which is aimed at rewarding bidder i in the jth auction based on its bidding prices and auction results in previous auctions using the following relationship score S_{ij}:

$$S_{ij} = B_{ij} + \alpha W_{ij} \qquad (1)$$

B_{ij} denotes bidder i's relative bidding price competitiveness until jth auctions. Hence, B_{ij} is the cumulative value of bidder i's price competitiveness compared to all remaining bidders' sum of average price competitiveness until auction j. We use just cumulative value of bidder's price competitiveness rather than average term in the numerator to reflect the changes in bidding price auction by auction more. It is defined as follow for each bidder i in kth auction;

$$B_{ik} = \frac{\sum_{j=1}^{k-1} f(b_{ij})}{\sum_{i=1}^{n_k} \left(\frac{\sum_{j=1}^{k-1} f(b_{ij})}{k-1} \right)}$$

Where $f(b_{ij})$ represents the *Price Competitiveness (PC)* transfer function. We set the price competitiveness based on each bidder's bidding price. Basically, the function gives a higher value to a lower bidding price. Furthermore, price competitiveness values for the bidding prices increase slowly as the price decreases, where bidding price is lower than certain point (termed as the turning point price) which is decided by auctioneer (for example, 10 in Figure 2). On the other hand, the price competitiveness value for the bidding price higher than certain point will be decrease rapidly. Figure 2 shows example of price competitiveness transfer function used in our experiment in section 5.

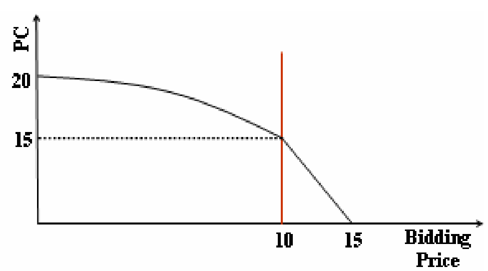

Figure 2. Example of price competitiveness transfer function

Second term in equation (1), W_{ij} stands for the bidder i's rewards from auctions until auction j. Hence, W_{ij} represents simply the cumulative number of wins for bidder i until j-1th auction in our model. It is defined as follow in kth auction;

$$W_{ik} = \sum_{j=1}^{k-1} w_{ij}, \text{ where } w_{ij} = \begin{cases} 1, & \text{if bidder } i \text{ wins in } j\text{th auction} \\ 0, & \text{otherwise} \end{cases}$$

The coefficient α in equation (1) controls the value of W_{ij} and its value is always negative in order to give more winning chances to bidders who have not been winning. If α is set as a more negative value, our scoring model gives more weight in W_{ij} and finally bidders who have yet to win for a long time will have a higher chance to win with their higher score, vice versa.

The relationship score S_{ij} of a bidder i in the auction j represents the bidder i's difference between the cumulated relative competitiveness of bidding price and the number of wins until the jth auctions. Hence, our bidder relationship scoring model is based on the insight that gives higher score to the bidder who has bidden relatively competitive bidding price but comparatively less wins so far. We argue that this kind of bidder has high possibility to drop out of future auctions.

4.2 Winner Determination

In winner determination, we consider not only the bidders' bidding price but also the scores obtained from relationship scoring model, thereby resulting in a winner determination problem with two criteria. There are well-studied approaches to solve multiple criteria optimization problems, for example in evaluating and selecting suppliers (Weber and Desai 1996, Talluri and Ragatz 2004, Beil and Wein 2003). In this study, we propose a winner determination algorithm based on a very general multi criteria decision making paradigm Data Envelopment Analysis (DEA) (Charnes, Cooper and Rhodes 1978, Webber 1996).

In our winner determination algorithm, we choose a single winner based on two inputs; the bidder's bidding price and its relationship score. First, we identify an efficient Pareto frontier which includes bidders who dominate other bidders from the observed inputs. Then, to assign the winner among the Pareto frontier, we apply an addictive model. Our winner determination algorithm is presented as follows:

[*Winner determination algorithm*]

Step 1. Find the Pareto efficient frontier and let the number of bidders on this frontier in auction j be n_j*

Step 2. Compare n_j* with 1(single winner)

2.1 if $n_j^* > 1$, go to Step 3

2.2 if $n_j^* = 1$, go to Step 4

Step 3. Select the winner among the n_j* bidders with the highest value U_{ij} (defined as follows) and go to Step 4.

$$U_{ij} = \beta \frac{b_{ij}}{\sum_{i=1}^{n_j} b_{ij}} + (1-\beta) \frac{S_{ij}}{\sum_{i=1}^{n_j} S_{ij}}$$

Step 4. Return the winner assignment result and stop.

Step 3 gives the formula to pick the winner among the Pareto frontier, where β is relative weight for bidding price against relationship score. U_{ij} is thus the weighted average of the normalized associated bidding price and score for each bidder i in auction j. In our experiments (presented in Section 5), we will analyze the impact of various β values on the auction results.

5. EXPERIMENTS AND RESULTS

In this section, we show how our Relationship Preserving Auction mechanism with bidder relationship scoring model and proposed winner determination algorithm works in various situations compared to other procurement auction mechanism prevailing in the market. The experiment in this paper is at the preliminary stage and the generated experiment data is based on empirical study from iMarketKorea which is procurement outsourcing company in Korea and our several assumptions. From the experiment results, we show the circumstances in which our proposed mechanism performs better than the conventional approach. Empirical validation for the experiment data and results will be needed in future studies.

5.1 Comparison Experiment Design

To compare our proposed auction mechanism with other approaches, we will use two comparison criteria;

- The auctioneer's total cost of procurement within the procurement time horizon with multiple auctions
- The number of bidders remaining in the last auction

We design the comparison experiments based on two factors; auction type and with/without bidder drop-out, as summarized in Figure 3.

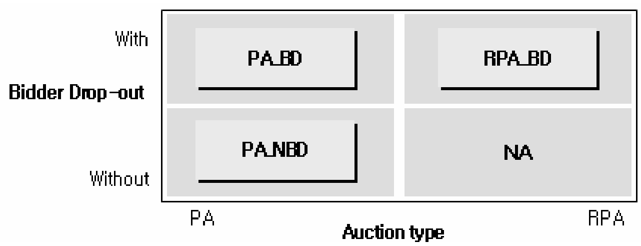

Figure 3. Comparison experiment design

RPA is not applicable in market which bidder never drops. More explanations for three schemes are given as follows:

1. **PA_NBD (Procurement Auction with No Bidder Drop)**: basic procurement auction (first price sealed bid reverse auction) with no possibility of bidders dropping out of auction over time.
2. **PA_BD (Procurement Auction with Bidder Drop)**: basic procurement auction, where bidders are allowed to drop out of auction at any time (based on some predefined bidder drop-out threshold)
3. **RPA_BD (Relationship Preserving Auction with Bidder Drop)**: our proposed Relationship Preserving Auction, where bidders are also allowed to drop out of auction at any time.

Note that PA_NBD is used only as a benchmark to obtain lower bound of auctioneer's total procurement cost, since no bidder drop in this repeated auction market is unrealistic.

The experiment auction platform is implemented in Java and run on a 2GHz PC with 1GB RAM.

5.2 Experiment Settings

To design a realistic experiment, we have conducted an empirical study from IMK to derive the parameters of data generation model.

5.2.1 Auctioneer Settings

One auction experiment case includes 30 repeated auctions as one procurement time horizon. Each auction will declare a single winner. The auction amounts are assumed as equal for all auctions. The Price Competitiveness (PC) transfer function: $f(b_{ij})$ is defined as below;

$$f(b_{ij}) = \begin{cases} 45 - 3 * b_{ij}^2, & b_{ij} \leq 10 \\ 20 - 0.05 * b_{ij}, & otherwise \end{cases}$$

The turning point price of 10 is selected arbitrarily compared to all the bidders bidding price range from the bidders settings.

5.2.2 Bidders Settings

Under the first price rule, if a bidder bids his cost, he earns zero profit and also forfeits the opportunity of profiting from subsequent markets. Hence bidders will markup their bids opportunistically, recognizing that, if they win, it can be more profitable (Hao 2000). Hao (2000) presented key factors affecting an opportunistic bidding strategy: the cost distribution of all bidders, market demand, and the number of bidders participating in the auction. Since information on competing bidders' cost distribution and the exact market demand are hard to come by, we do not assume such information is available. We do however assume that the number of participants is revealed to bidder just like other auction studies (Harstad et al. 1990). Based on given information and bidder's own information about its cost and performance in previous auctions, we create bidder *i*'s bidding price in auction *j*, as follows:

Equation (2): $$b_{ij} = c_{ij} + c_{ij} * \{\delta(\frac{W_{ij}}{m} + \frac{1}{n_j})\}$$

Where c_{ij} is bidder *i*'s cost for the item in the auction *j*, *m* represents the number of auctions in the time horizon, and n_j is the number of participants in auction *j*. In this experiment, we assume that every bidder's bidding prices are generated from equation (2) with different cost and coefficient (γ) values.

Equation (2) means that bidders generate their bidding price based on the number of wins so far as well as the number of participants in current auction. This bidding generation method is rational and intuitive. If bidders keep winning in the auctions, they will tend to increase the bidding price, because they gather that their bidding price is quite competitive, vice versa. Hence, we use the term W_{ij}/m in equation (2).

And if the number of participants is relatively small, which means it is a less competitive environment, bidders will bid more aggressively. $1/n_j$ in (2) represents this effect in generating bidding price.

γ is the coefficient that controls the level of bidder's opportunism in generating bidding price. For the experiments, we set γ from

0.1 to 0.5. Hence, possible bidding price for bidder *i* is higher than cost and less than twice of the cost.

We assume that each bidder has different cost structure based on its production volume and competency in the market. Further more the cost changes along time period and the range is also different among bidders. The bidder *i*'s cost in auction *j* (c_{ij}) is randomly generated over a uniform distribution within the range as follows: bidder 1: [7,9], 2:[8,10], 3:[8,11], 4:[8,11], 5:[9,11], 6:[9,12], 7:[10,13]. Bidder with lower number has less cost than bidder with higher number.

We define the bidder *drop-out threshold* as the maximum number of consecutive losses (i.e. no wins) bidders experience before dropping out of the auction. The drop-out threshold of each bidder is uniformly distributed over the range [6, 10] during one auction case with 30 repeated auctions. For PA_NBD, this value is simply set to be larger than the number of auctions.

For each experiment set, we generated 30 different auction experiment cases. Our experiments proceed and show the results as follows in section 5.3. First, we conduct experiments to find optimal value for the coefficients α and β in the given settings. Based on the results, we compare three different auction mechanisms in terms of average total cost of procurement for auctioneer and average number of remaining bidders in the last auction from the experiment set. We investigate further how RPA_BD reduce total procurement cost in repeated auctions. This is followed by experiments results under specific bidders' bidding behavior allowing us to conclude with precise conditions which RPA_BD performs well. In section 5.4, we summarize the experiment results and discussions.

5.3 Experiment Results

5.3.1 Optimal Value for the Coefficient

The coefficient α in equation (1) controls the value of W_{ij} and its value is always negative in order to give higher chances to bidders who have won relatively less frequently. Note that the more negative the value of α, the higher impact of W_{ij} on the relationship score, and consequently the more bidders (including less competitive bidders) will be maintained in the system, and vice versa. We set β as 0.5 and test the effect of α on the average total cost of procurement. The value of α is selected within [-3, 0] and Figure 4 shows the results.

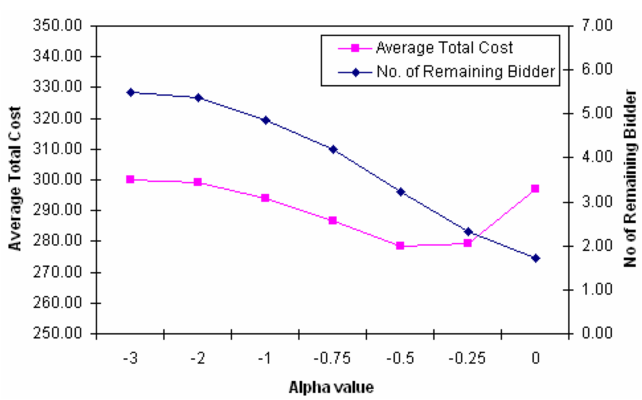

Figure 4. Optimal value of α

As α decreases from -0.5, the average total cost increase by maintaining larger number of bidders including less competitive bidders. If α is smaller than -2, there is no much change in terms of average total cost and number of remaining bidders. When α is bigger than -0.5, the average total cost also increase because only few number of bidders remain. The average total cost has lowest value when α is -0.5. Hence, we set the optimal α value as -0.5 in this experiment.

β is the coefficient used in winner determine process - it represents the weight for current bidding price while (1- β) is for relationship score. We compare the results of RPA_BD and PA_BD through various β values from 0 to 1 by setting α as -0.5.

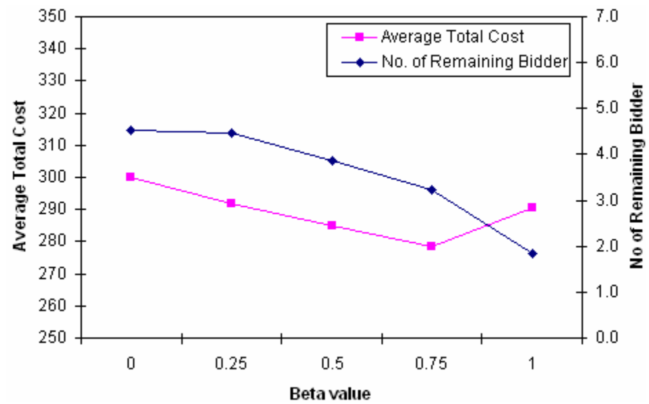

Figure 5. Optimal value of β

When β =1, the result of RPA_BD is as same as PA_BD because only bidding price is considered in winner determination. RPA_BD obtains lowest average total cost where β=0.75. If β decrease from 0.75, the average total cost increasing by keeping more bidders. That means, there is a chance to keep too many bidders including less competitive bidders if we give more weight to relationship score in winner determination process. In this auction experiment, we set the optimal β value as 0.75.

5.3.2 Comparison Results

In this section, we compare three different auction mechanisms based on generated experiment data where α= -0.5 and β=0.75. Table 1 summarizes the results.

Table 1. Comparison results

PA_NBD		PA_BD		PRA_BD	
No. of Remaining Bidders	Avg. Total Cost	No. of Remaining Bidders	Avg. Total Cost	No. of Remaining Bidders	Avg. Total Cost
7	262.37	1.83	289.73	3.23	278.62

PA_NBD provides the lower bound of average total cost. Average total cost from RPA_BD is 5.8% higher than PA_NBD. Between RPA_BD and PA_BD, RPA_BD saves average total cost by 4% compared to PA_BD. 4% cost saving from one item procurement has huge impact on procurement outsourcing company. RPA_BD can save average total cost keeping enough number of bidders for competitive bidding price to the last auction. Number of remaining bidders from RPA_BA (3.23) is larger than from PA_BD (1.83).

We further investigate the reasons for the difference between RPA_BD and PA_BD. According to our proposed mechanism, RPA_BD gives more chances to win for relatively competitive bidders efficiently and maintaining enough bidders for competitive bidding price until last auction. On the contrary, only few bidders win the most auctions in PA_BD and they will increase their price after other bidders dropped out of the auction. Eventually, only few bidders take most benefits from auction and auctioneer pays more eventually. To verify this argument, we compare number of wins of each bidders and Figure 6 shows the winning distribution among 7 bidders through 30 experiment cases.

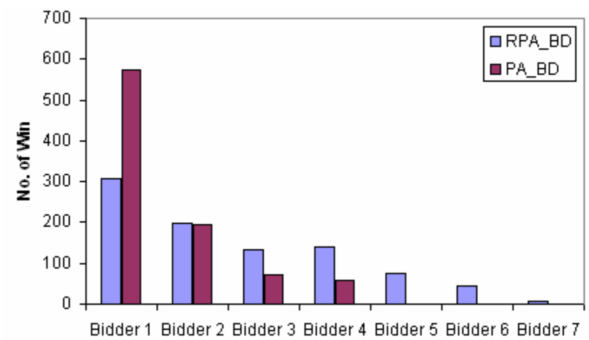

Figure 6. Winning distribution: RPA_BD vs. PA_BD

As we expected, RPA_BD gives a higher chance to the bidders efficiently according to their bidding competitiveness. Bidders with lower number have less cost and they bid more competitively based on bidding price generation method. From the Figure 6, our mechanism allocate winner efficiently based on bidders' bidding competitiveness. In PA_BD, most of wins are allocated to the small number of bidders and it will increase the auctioneer's procurement cost. By analyzing the winning price at each auction between RPA_BD and PA_BD, we can show more clearly why RPA_BD decrease the auctioneer's procurement cost compared to RA_BD. Figure 7 depicts the winning price along 30 repeated auctions in one particular experiment case where each bidder's drop-out threshold is set 7,9,9,10,9,7,6 respectively.

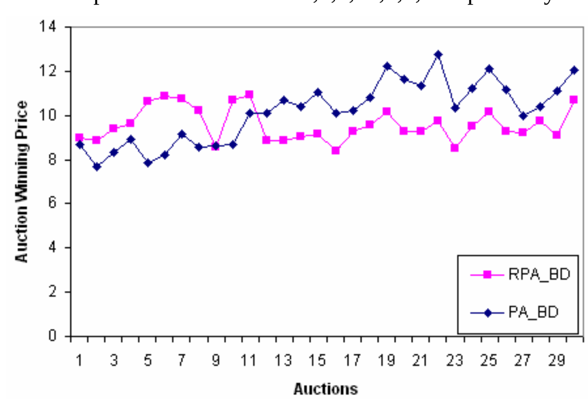

Figure 7. Winning price distribution: RPA_BD vs. PA_BD

In earlier auctions, the winning price from PA_BD is less than RPA_BD. However, after certain number of auctions, the winning price of PA_BD keeps increasing because a small number of remaining bidders bid opportunistically according to the bidding price generation method. On the contrary, the winning price from RPA_BD is consistent with a larger number of bidders retained until last auction. PA_BD retains two bidders, while 4 bidders remain in RPA_BD.

5.3.3 Under Different Bidding Behavior: Bidding Price Generation

In this section, we compare the auction schemes with different levels of opportunism (γ) in biding price generation. Note that the higher γ value means bidders bid more aggressively as the opportunity for winning increases. That means it will increase the total cost of procurement for the auctioneer eventually. We assume that all bidders have equal γ value within each experiment set, and we test 5 different γ values such as 0.1, 0.2, 0.3, 0.4, 0.5 respectively. Figures 8 and 9 show the results.

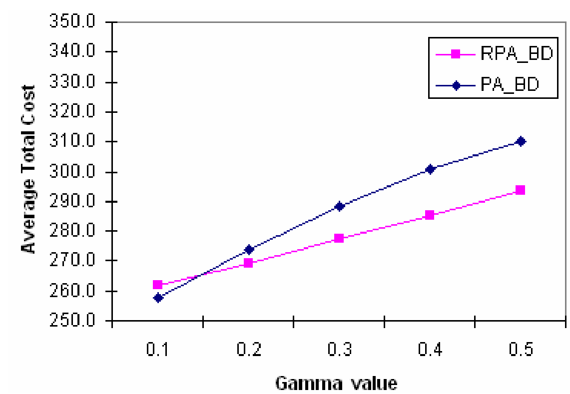

Figure 8. Average total cost vs value of γ

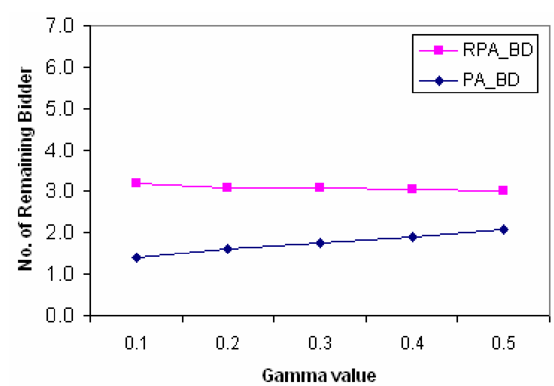

Figure 9. Number of remaining bidders vs γ

As the γ value increases beyond a certain point, the average total cost derived from RPA_BD becomes less than PA_BD. That means, RPA_BD performs better when bidders bid more opportunistically as the opportunity of winning increases.

5.3.4 Under Different Bidding Behavior: Drop-out Behavior

We compare the average total cost and number of remaining bidders based on the effects of different drop-out thresholds. We assign the same drop-out threshold for 7 bidders that range from 3 to 30. We compare RPA_BD and PA_BD in different bidder drop-out thresholds and Figures 10 and 11 summarize the results in terms of the two evaluation criteria.

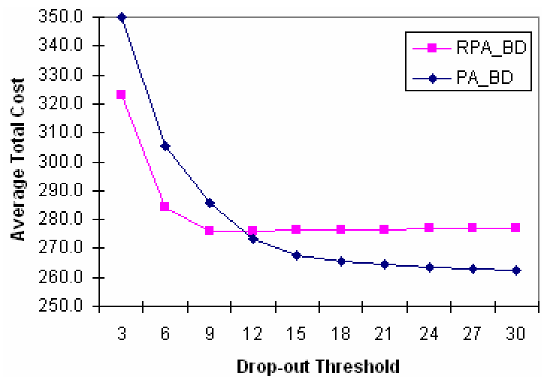

Figure 10. Average total cost vs Drop-out threshold

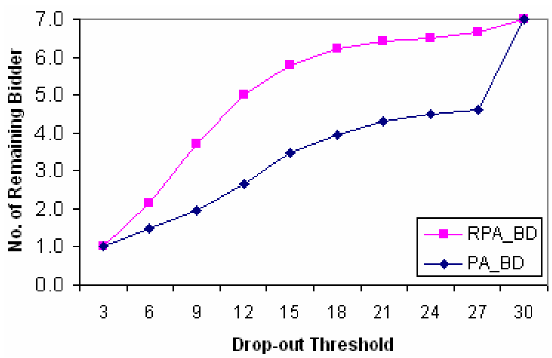

Figure 11. Number of remaining bidders vs Drop-out threshold

After the drop-out threshold of 12, PA_BD produce less average total procurement cost than RPA_BD. By increasing the drop-out threshold, the number of remaining bidders increase and it affects the bidding price finally. From this result, we can conclude that if bidders are less likely to drop out of the auction market, there is less need to use RPA_BD to maintain more bidders. Hence, RPA_BD works well in auction markets where the participating bidders are readily to quit the market if they keep losing.

5.4 Discussion

From the above experiments, we conclude that our RPA_BD mechanism works well under specific conditions in which participants exhibit certain level of opportunistic bidding behavior and bidders readily drop out of the auction after a certain number of consecutive losses. RPA_BD keeps enough bidders by giving more chance to relatively competitive bidders and bidders will bid competitively until the last auction. Eventually, it decreases the procurement cost of auctioneer in our experiments.

We believe that using our proposed auction mechanism will be beneficial to the procurement outsourcing company which deals with standardized products where there are many suppliers and many parallel markets, where suppliers are loosely coupled with the auctioneer in the sense that they can renege and move to other markets if the current market is not profitable. Such markets are becoming very common with the increasing popularity of online auctions (Jap 2002).

6. CONCLUSION

E-procurement auction has become a dominant procurement strategy in many industries. While the adoption of e-procurement auction has helped firms to obtain lower cost procurements, it has also raised important issues related to maintaining long-term relationships with the partners, especially in a repeated e-procurement context. In this paper, we proposed the notion of Relationship Preserving Auction which we realize through a relationship scoring model. Our experiments show that our approach can perform better than typical procurement auctions in repeated auctions under specific conditions - where bidders bid opportunistically and quite the auction market readily after certain number of consecutive losses. RPA_BD achieve these results from keeping enough bidders by giving more chance to relatively competitive bidders. Bidders will bid competitively until the last auction and it decreases the procurement cost of auctioneer in our experiments eventually.

However, findings from our experiments are based on several assumptions and simplification. One extension from our work is further investigations on bidders' bidding behaviors in real procurement auctions. Another aspect of our approach is that it deals with a closed set of bidders, and does not allow entrance of new bidders throughout the time horizon. An interesting extension is to hence deal with a dynamic setting where bidders can join and leave the system.

This paper focuses on the auction setting for a single item with single winner. An open research topic is to consider multiple items with multiple units. One approach is to decompose into multiple simultaneous auctions, so long as the items are not combinatorial in nature. Even if they are, our approach still works if we extend our proposed winner determination algorithm to handle combinatorial auctions.

We also recognize the need to consider not only competitiveness of bidding price but also bidder's quality such as product quality, delivery accuracy to generate more complete relationship in further studies.

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